Syllabus

DESCRIPTION AND LEARNING OBJECTIVES

Credits: 3
Instructor's name: Manel Martínez-Ramòn
Additional information:

a. Office Location: 237b
b. Office Hours: MO-WED 11:00 to 12
c. Class Meeting Day(s): TR
d. Class Location / Room: ME 210
e. Email: manel@unm.edu
f. Office Phone: (505) 277-3008
g. Class Time: 9:30 to 10:45
h. Term / Semester: Fall

This class covers several advanced topics in machine learning, including statistical learning theory, kernels, gaussian processes and ensemble learning. The course opens with an introduction to the basics of Statistical Learning Theory, that leads to the well known SVM. Here, the SVM principle is taken as an optimization criterion that can be applied virtually to any linear algorithm. For Dimensionality Reduction, the SVM will be used as a particular technique for feature extraction or dimensionality reduction strategies. Block Reproducing Kernel Hilbert Spaces will be used to provide an introduction to kernel methods, and a view of kernels as a similarity measure tool that allows us to generalize any linear algorithm by extending them with nonlinear properties. In particular, some LS algorithms and SVMs will be extended to the nonlinear case. Also, we will go deeper in the concept of regularization already introduced in first part of the course. In the section on Gaussian Process Networks, we will introduce an alternative criterion, based on ML particularly successful for regression, that will be generalized using kernels. Finally, Ensemble Learning Machines will be reviewed as a third major set of algorithms widely used in machine learning besides deep learning, which is beyond the objectives of this class.

This graduate-level class will provide students with a strong foundation for both applying machine learning to complex real world problems and for addressing core research topics in machine learning. Student taking the class should have the prerequisite undergraduate knowledge of probability, statistics and, linear algebra. The background material will also be reviewed in the course.

MATERIALS, TOPICS AND ASSESSMENT

Textbook

The topics of this course are not covered by a single book. Students will find all the materials in three different ones. The books are written by some of the original authors of the topics (Hastie and Tibshirani, Shawe-Taylor and Cristianini. Rasmussen and Williams). Two of the books are released their works for free access., and the other is available online for all UNM students. This means that while materials are mandatory, students are not forced to purchase the rather expensive books, but they can use the online versions for free.

The Elements of Statistical Learning, T. Hastie et al., Springer, 2009 Available online, free access.

Kernel Methods for Pattern Analysis, J. Shawe-Taylor, N. Cristianini, Cambridge University Press, 2004. Available online through UNM Libraries

Gaussian Processes for Machine Learning, C. Rasmussen et al., MIT Press, 2006 (Available online, free access)

Other supplemental materials:

- "A Tutorial on Support Vector Machines for Pattern Recognition", by Christopher Burges

Specific course information

1. Brief description of the content of the course (catalog description).
   This course covers topics in machine learning, including statistical learning theory, kernels, Gaussian processes and deep learning. The course opens with an introduction to the basics of *Statistical Learning Theory*, that leads to the well known SVM. Here, the SVM principle is taken as an optimization criterion that can be applied virtually to any linear algorithm. For *Dimensionality Reduction*, the SVM will be used as a particular technique for feature extraction or dimensionality reduction strategies. Block *Reproducing Kernel Hilbert Spaces* will be used to provide an introduction to kernel methods, and a view of kernels as a similarity measure tool that allows us to generalize any linear algorithm by extending them with nonlinear properties. In particular, some LS algorithms and SVMs will be extended to the nonlinear case. Also, we will go deeper in the concept of regularization already introduced in first part of the course. In the section on *Gaussian Process Networks*, we will introduce an alternative criterion, based on ML particularly successful for regression, that will be generalized using kernels. Finally, *ensemble learning machines (adaptive basis function models)* will be reviewed as a third major set of ML algorithms.
2. Prerequisites or co-requisites
   Student taking the class should have knowledge of probability, statistics and, linear algebra. The background material will also be

reviewed in the course. Also, it is mandatory to have basic knowledge of Matlab, Phython or similar language programming.

Specific goals for the course

This graduate-level class will provide students with a strong foundation for both applying machine learning to complex real world problems and for addressing core research topics in machine learning.

Topics covered

Introduction

Statistical learning theory.

- Estimation function and risk minimization.
- Definition of learning problems: classification, estimation, unsupervised learning.
- Empirical risk minimization. The generalization ability of a learning machine.
- Consistency of learning.
- VC dimension and the structural risk minimization.
- The Support Vector Machine approach. Detailed derivation. SVC, SVR, SVDD, variants.
- Optimization procedures.

Reproducing Kernel Hilbert Spaces.

- Overview
- Positive definite kernels.
- Main theorems. The kernel trick.
- Kernel based learning machines.
- Some basic kernels and kernel properties
- Kernel development and special kernel classes.

Gaussian Process Networks

- Basic concepts.
- Gaussian process networks for regression and classification.
- Kernel versions of the GPN.
    - Dual formulation of the GPN.
    - The idea of covariance matrices.
- Parameter optimization and model selection.

Adaptive Basis Function Models.

- Introduction.
- Trees.
- Random forests.
- Boosting.

Assignments and software

A number of assignments will be required. They will be published at the beginning of the course, through UNMLearn. Their due dates will be posted.

Experimental projects will be accepted in any platform, but the use of Matlab, Julia or Python is strongly advised.

Assessment and grading policy

- Homework: at least 90%. Must be delivered before the deadlines. The homework will be graded following the corresponding rubric.
- Quizzes: at most 10%. The deadlines for the quizzes are the same as for the homework.

Deadlines cannot be negotiated. Students turning in homework after the deadline will not be graded.
Students choosing the grade/no grade option will be also required to deliver the homework. Audit students are welcome upon proper UNM registration.

Attendance Policy
Regular and punctual attendance is required. UNM Pathfinder policies apply, which in part means instructor drops based on non-attendance are possible. This policy applies regardless of the grading option you have chosen.

Accommodation Statement
Accessibility Services (Mesa Vista Hall 2021, 277-3506) provides academic support to students who have disabilities. If you think you need alternative accessible formats for undertaking and completing coursework, you should contact this service right away to assure your needs are met in a timely manner. If you need local assistance in contacting Accessibility Services, see the Bachelor and Graduate Programs office.

Academic Integrity
The University of New Mexico believes that academic honesty is a foundation principle for personal and academic development. All University policies regarding academic honesty apply to this course. Academic dishonesty includes, but is not limited to, cheating or copying, plagiarism (claiming credit for the words or works of another from any type of source such as print, Internet or electronic database, or failing to cite the source), fabricating information or citations, facilitating acts of academic dishonesty by others, having unauthorized possession of examinations, submitting work of another person or work previously used without informing the instructor, or tampering with the academic work of other students. The University's full statement on academic honesty and the consequences for failure to comply is available in the college catalog and in the Pathfinder.

Cell Phones and Technology
As a matter of courtesy, please mute cell phones, pagers, and other communication and entertainment devices prior to the beginning of class. The use of cell phones or other devices to chat, browse the Internet or for any other purpose during the class should be avoided. Notify me in advance if you are monitoring an emergency, for which cell phone ringers should be switched to vibrate.